Dynamic Programming for Multi-Crew Scheduling of the Emergency Repair of Network

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Abstract One of the most necessary operations in humanitarian logistics is the distribution of relief goods to the population in disaster areas. When a disaster occurs, some parts of the distribution infrastructure may be damaged and consequently make it impossible to reach all the demand nodes and delivering the relief goods. In this study, we focus on the planning of infrastructure recovery efforts in post-disaster response. The problem is the scheduling of the emergency repair of a network that has been damaged by a disaster. The objective is to maximize network accessibility for all demand nodes in order to deliver relief goods to them. We adopt a dynamic programming algorithm to solve the problem when more than one crew group is available. Our numerical analysis of the solution shows the performance of the algorithm. We, also, compare our results with some similar studies to indicate the differences between one and multi-crew scheduling.

Keywords *Network Repair, Repair Crew Scheduling, Dynamic Programming, Multi-Crew Planning*

Introduction

Based on the International Federation of Red Cross and Red Crescent Societies (IFRC) definition, a disaster is a sudden, calamitous event which seriously disrupts the functioning of a community and causes human, material, and economic or environmental losses that exceed the community's ability to cope with using its own resources (IFRC, 2012). Almost 2.7 billion people have been affected, 1.1 million killed and damage of 1.3 trillion dollars has been reported worldwide due only to natural disasters (United Nations Office for Disaster Risk Reduction, 2012). On the other hand, additional thousands of affected and dead people are consequences of technological disasters, which are the result of man-made product failures (Hoyos et al. 2012). The global growing trend in large-scale natural disasters and affected people number, leading to a greater need for efficient disaster management. A framework for disaster operations and associated flows and facilities are developed by Caunhye et al. (2012) which is shown in Figure 1.
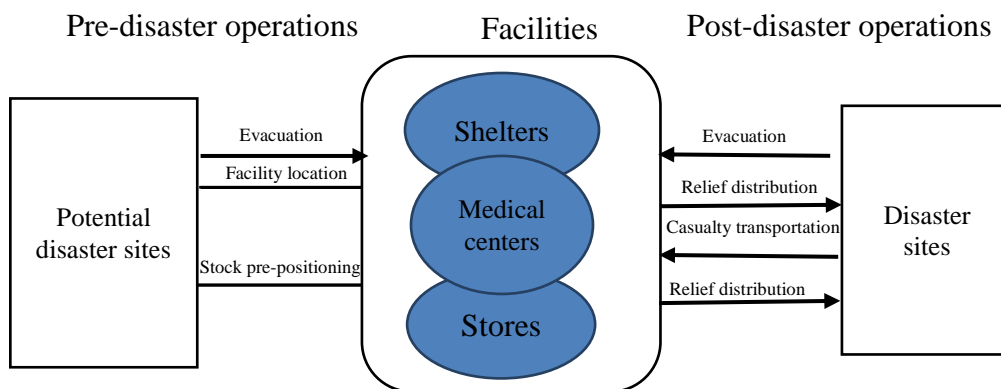

Figure 1.
A Framework for Disaster Operations (Caunhye et al., 2012)

Note that, all the post-disaster operations are dependent on infrastructure availability. So if some roads are damaged by the disaster the demand nodes cannot be reached. Therefore we suggest that road recovery be added to the post-disaster operations in Fig 1. Hence one of the main issues affecting the food, shelter, and medical supplies delivered to disaster areas is the state of the road network. In many situations, it is not a lack of supplies that kills people, but the impossibility to get those supplies to the people that need it. In Haiti, for example, extensive media coverage of the 2010 earthquake resulted in a large excess stock of relief supplies. Up to now, emergency repair and relief distribution planning have traditionally been done manually and separately, based on the decision-maker's experience, disregarding the interrelationship between emergency repair and relief distribution from the system perspective. For emergency repair scheduling, the repair points are first separated into several groups, each associated with a nearby work station. Note that, a repair point is a particularly damaged segment of the roadway that needs to be repaired. The repair schedule is determined manually for each group, and is theoretically only a feasible solution. Consequently, the resulting solution could possibly be inferior. Since rescue resources are often inadequate due to emergent conditions after a major disaster, how to most efficiently use these limited resources is very important and has an impact on emergency rescue effectiveness and damage reduction. Hence, this research tries to develop a model, with the objective of minimizing the length of time for both an emergency repair and relief distribution to help efficiently set schedules for both within the shortest possible period of time. In this paper, the problem of scheduling the emergency repair crew of a rural road network that has been damaged by the occurrence of a natural disaster is considered. The network repair multi-crew scheduling addresses the scheduling of multi repair crew, starting from a single depot, while optimizing accessibility to the disaster areas which need relief goods.

Literature Review

New emergency logistics activities were primarily concerned with relief distribution, stock pre-positioning, facility locations, evacuation and transfer of wounded people and modeled the combination of relief commodity flows and resource allocations (Jin et al., 2015). Two stochastic programming models have been designed by Chang et al. (2007) for urban flood disasters which regulate the plans for rescue resource distribution that involve the location of rescue resource warehouses, the structure of the rescue organization, the distribution of rescue resources and the rescue resources allocation with capacity constraints. A time minimization model is considered by Duran et al. (2011) to enhance operations in organizations. An approach that is a two-stage stochastic model for distribution and storage of medical supply is presented by Mete and Zabinsky (2010). According to their stochastic approach, in the first stage the inventory levels and warehouse selections are determined and in the second stage transportation plans are determined. Also, Rawls and Turnquist (2010) proposed a two-stage stochastic mixed-integer problem that considers the uncertainty of the input values. In the first stage, in the existence of network damages and demand variations, a decision is made. The decision of the second-stage is conditional on the first stage decision and is made after the random problem elements. Sheu (2007) developed an approach that hybrid fuzzy clustering optimization for activities of emergency logistics. Ozdarmar et al. (2004) incorporated the vehicle routing problem into the process of relief distribution. In their model vehicles are considered as commodities in order to simplify decomposing the problem of detailed emergency logistics distribution into two multi-commodity network sub-problems. Yi and Ozdamar (2007) have extended this approach to an integrated location–distribution problem for evacuation activities and coordinating logistics support in disaster response operations.

Barbarosoglu et al. (2002) proposed a bi-level hierarchical decomposition approach for helicopter mission planning within a disaster relief activity. Altay and Green (2006) and Ergun et al. (2010) highlight that disaster recovery, i.e., the planning of actions taken during the "reconstruction phase", is one of the main areas in which more research is needed. We can find in the literature some studies on emergency repair such as Tamura et al. (1994), Chen and Tzeng (1999), Fiedrich et al. (2000), Feng and Wang (2003). A recent survey by Kunz and Reiner (2012) confirms that "only ten papers specifically address the reconstruction phase" and stresses the importance of this stage by stating that "the quality of the logistical activities during this phase strongly impacts the success of the whole disaster recovery process, especially in terms of sustainability and long-term effectiveness (Beamon & Balcik, 2008; Benson, Twigg, & Myers, 2001; Besiou, Stapleton, & Van Wassenhove, 2011; Kovács & Spens, 2011). Some researchers such as Sohn (2006) and Jenelius and Mattsson (2012) identify the importance of network links/areas by evaluating accessibility measures by closing one link/area at a time and observing its impact on the whole network. Chen and Tzeng (2000) propose a two-level mathematical model for sequencing road repair tasks over time, imposing a due date. Travel times between tasks are considered but repair resources are not limited. The goal is to minimize travel weighted traffic flow. The model is quite complex, therefore, a genetic algorithm is proposed. In another study, the authors use a multi-objective GA to solve the same problem on a realistic network with 24 nodes. Yan and Shih (2009) propose an integrated road repair and relief distribution model with the goal of minimizing operation completion time. A time augmented network flow model with work team trips and relief material flows (over repaired roads) is proposed with an equity constraint on demand satisfaction. A three-step heuristic is proposed: blocked links are prioritized; worker schedules and

commodity flows are optimized. A 46 node network with 25 repair points is solved for a 3-day span with a time bucket of 15 min. Due to model size, this small network is solved in 900 CPU seconds. Matisziw and Murray (2009) identify vital node and arc blockages that would prevent traffic flow the most with both mitigation and response intentions (to protect most critical linkages in the pre-disaster phase and recover them first in the post-disaster phase). The authors maximize flows over broken source-sink paths while identifying the most critical k links. The introduction of path aggregation constraints disposes of the necessity to enumerate all source-sink paths. Results of the model are illustrated on a network of 23 nodes and 34 arcs. In an earlier study, Murray et al. (2007) propose a similar model that identifies the most critical links that make a set of k facilities inaccessible. This model is tested on a fiber-optic communications network. Maya Duque and Sörensen (2011) address the repair problem under budget constraints using a fixed cost network flow formulation for minimizing the cost of flows from each rural center to the nearest regional center. Tahanian and Khaleghi (2015) proposed a genetic algorithm to a manpower-scheduling problem arising at a Petrochemical Company. In the proposed algorithm, the indirect coding based on permutations of the personnel's, and a heuristic decoder that builds schedules from these permutations were used. Molaei et al. (2016) considered the scheduling of preventive maintenance problem with total cost and total reliability of the system. Due to the uncertainty in the input parameters, they proposed a robust approach to solve the multi-objective model. In this paper, a genetic algorithm was applied to achieve the Pareto layer.

Problem Definition

The problem is similar to the problem defined in Maya Duque et al. (2016) but here we consider more than one repair crew. The problem is

defined on an undirected and connected graph $G = (V, E)$ of which the nodes (V) are either demand nodes (V_d) or damaged nodes requiring repair (V_r). A damaged road link is represented by a node located in the middle of the corresponding link. Therefore, repairing a road connection is equivalent to repairing a node, and we use the two terms interchangeably. There is one supply node which is denoted by node 0 and corresponds to the location in which the relief supplies are positioned and from which the repair crews initially depart. This node is called the depot. Demand nodes are locations that need relief goods. Weight factor w_i, shows the importance of a demand node. Damaged (repair) nodes that have zero demand indicate the locations where the work of the repair crew is needed and in these nodes, the time the repair crew spends to repair the node is shown by a repair time s_j (for node j). Also, we do not distinguish between demand nodes and transshipment nodes, and we model the transshipment nodes as demand nodes with zero demand. Each edge $e_{ij} \in E$ is a link that connects two nodes i, $j \in V$. The time that takes the repair crew to traverse a link is defined by t_{ij} (travel time) for each e_{ij}.

Every time a crew visit a damaged node, they repairs this node and a repair time is spend on this node. On subsequent visits the crew can pass that node without spending any repairing time. Demand nodes can become accessible when damaged nodes are repaired. In the other hand, a demand node i is called accessible, if a path exists that connecting this node to the depot with only undamaged and/or repaired nodes and is not longer than a certain maximum distance D_i. The maximum distance D_i is node-specific and can be computed based on pre-disaster conditions. Thus, in addition to the travel time t_{ij}, each edge e_{ij} has a distance measure, denoted d_{ij}, that is used to evaluate nodes' accessibility. For each demand node, the schedule of the crews determines the moment in time at which this node becomes accessible. The objective function of the problem is the sum of the moments at which

each demand node becomes accessible weighted by the node demand w_i. The objective of the network repair problem is to determine the schedule of the repair crews that minimizes this objective function. In general, it is not necessary for the repair crew to visit all damaged nodes.

Dynamic Programming

In this section, we adopt The DP model presented by Maya Duque et al. (2016) to the situation when more than one repair crew is available. The DP model keeps track of the repair crew as it repairs one node in V_r after another, and makes sequential decisions on which node the crew should repair next. When a node is repaired, a subset of demand nodes that have not been accessible so far can become connected to the supply node, and a "cost" is incurred corresponding to the new satisfied demand weighted by the time when the connection is established. A constraint is implicitly included requiring to connect all demand nodes to the supply node, and the weighted time the algorithm connects all the nodes in V_d corresponds to the cost that is being minimized. Thus, the state of our model needs to keep track of the current time and location of the repair crew, as well as the subset of damaged nodes that have not been yet repaired, and the subset of demand nodes that are not yet accessible from the depot. Our DP formulation requires an additional auxiliary node $n + 1$ to be added to the graph. This node corresponds to a dummy depot connected to all the damaged nodes (i.e., nodes in V_r) through arcs with zero travel time. Note that, the DP model explicitly tracks the crew as it moves from one repair node to the next, while the fastest feasible paths between the repair nodes are calculated at each state transition to compute the corresponding travel time. Finally, we assume that the DP state is updated after the repair of the current node is completed. As mentioned before and the main contribution of this study, considering more than one repair crew is the

difference between this study and previous studies. So that before explaining the formulation of the DP we state some assumptions about the repair crews.

- Repair time (s_j) is the same for all the repair crews. It means that each crew spends the same time to repair a damaged node.
- Each crew goes to the nearest damaged node.
- At first, 2 repair crews dispatch to the 2 nearest damaged group.
- It is possible for a damaged node to be repaired by 2 repair crews simultaneously. This case often occurs for the last repair node in the network.

Formally, this problem can be expressed as a dynamic programming model as follows. Firstly we introduce the sets and parameters.

V	Set of nodes $\{0, 1, \ldots, n+1\}$; node 0 is the depot; node $n+1$ is a dummy node; $V = \{0\} \cup V_d \cup V_r \cup \{n+1\}$
V_d	Set of demand nodes; $V_d \subset V$
V_r	Set of damaged nodes requiring repair; $V_r \subset V$
E	Set of edges or road
e_{ij}	Edge connecting nodes i and j; $e_{ij} \in E$
$E(k)$	Set of arcs adjacent to node $k \in V, E(k) \subset E$
M	Set of repair crews; $m = \{1, \ldots, M\}$
w_i	Relief demand of node $i \in V$
t_{ij}	Time required to travel between nodes i and j on edge e_{ij}
s_j	Time required to repair damaged node $j \in V_r$
d_{ij}	Length of edge e_{ij} connecting nodes i and j, i.e., the distance between nodes i and j
d_e	Length of edge e

D_i Maximum acceptable distance from node $i \in V_d$ to the depot in order for i to be accessible to it

DP state: $s = (i_m, t_m, \overline{V_d}, \overline{V_r})$ where

$i_m \in (V_r \backslash \overline{V_r}) \cup \{0\} \cup \{n + 1\}$ current repair node location of the repair crew m

$t_m \geq 0$ current time of repair crew m

$\overline{V_d} \subseteq V$ demand nodes that are not yet accessible

$\overline{V_r} \subseteq V$ damaged nodes that are not yet repaired

DP action: $a = j_m$, corresponding to the decision for the repair crew m to move to node j, where, given the current state $s = (i_m, t_m, \overline{V_d}, \overline{V_r})$ the action space $A(s)$ is

$$A(s) = \begin{cases} \{j \in \overline{V_r} : \tau(i_m, t_m, \overline{V_r}) < \infty\}, if \overline{V_d} \neq 0 \\ \{n + 1\} if \ \overline{V_d} = 0 \end{cases}$$

Here, $\tau(s, a) = \tau(i_m, t_m, \overline{V_r})$ is the function that returns minimum travel time between nodes i_m and j_m over all the paths that do not pass through nodes in $\overline{V_r}$. The function returns infinity if no such paths exist. The fastest path problem from i to j for al $j \in \overline{V_r}$ can be solved efficiently with one execution of a Dijkstra's algorithm (Dijkstra, 1959), similar to the discussion of the accessibility function below.

DP state transition: $g(s, a)$ is the state transition function that returns a state to which the system transitions when action a is chosen in state s.

$s = (i_m, t_m, \overline{V_d}, \overline{V_r}) \rightarrow (i'_m, t'_m, \overline{V'_d}, \overline{V'_r})_{a = j_m}$

$i'_m = j_m$

$t'_m = t_m + \tau(i_m, t_m, \overline{V_r}) + s_j$

$$\bar{V}_d' = \bar{V}_d \backslash v(\bar{V}_d, \bar{V}_r, \sum_m j_m)$$

$$\bar{V}_r' = \bar{V}_r \backslash \{\sum_m j_m\}$$

Here, $v(s,a) = v(\bar{V}_d, \bar{V}_r, \sum_m j_m)$ is an *accessibility function* that returns a subset of nodes in $\bar{V}_d$ that become accessible when node $j \in V_r$ is repaired. Note that, $v(\bar{V}_d, \bar{V}_r, \sum_m j_m)$ can return an empty set when no new nodes are connected to the supply node by repairing node j. A set of shortest (distance) path problems on the updated network (where node j can be passed without incurring the repair cost) needs to be solved in order to evaluate $v(.)$. An efficient way to do so is discussed later in this section.

DP action cost: $c(s, a)$ is the instantaneous cost of action a when in state s, where for

$s = (i_m, t_m, \bar{V}_d, \bar{V}_r)$ and $a = j_m$ we have:

$$C(i_m, t_m, \bar{V}_d, \bar{V}_r, j_m) = t_m + \tau(i_m, t_m, \bar{V}_r) + s_j. \sum_{kv(\bar{V}_d, V_r, j_m)} w_k \tag{1}$$

Recursive equation: Let $f(s)$ denote the minimum cost incurred by the system reaching from the initial state $s_0 = (0,0, V_d, V_r)$ to the current state $s = (i_m, t_m, \bar{V}_d, \bar{V}_r)$. Then, we can write the following dynamic programming (Bellman's) recursive equation.

$$f(\acute{s}) = min_{\{s,s.t,g(s,a)=\acute{s}, a \in A(s)\}}(f(s) + C(s,a)) \tag{2}$$

where $f(s_0) = 0$. Recursively solving Eq. (2) we find the minimum value for

$$min_{\{s=(i_m, t_m, \bar{V}_d, \bar{V}_r), s.t, i=n+1\}}(f(s))$$

which corresponds to the minimum value of our problem objective function.

Accessibility function: Recall, $v(s, a) = v(\overline{V_d}, \overline{V_r}, \sum_m j_m)$ is an *accessibility function* that returns a subset of nodes in $\overline{V_d}$ that become accessible when node $j \in \overline{V_r}$ is repaired. This function can be efficiently evaluated as explained in Maya Duque et al. (2016).

There are a number of observations and problem structure properties we use to facilitate efficient implementation of the DP model. To initialize the DP recursive equation, the algorithm preprocesses the problem instance to find a more compact initial state than $s_0 = (0,0, V_d, V_r)$. We Note that, in a given instance, a number of demand nodes can maintain their accessibility despite the damage to the road network, and s_0 does not need to include all the nodes in V_d. Thus, the shortest path algorithm is run on the damaged network (i.e., no nodes in V_r are assumed to be repaired) to find the minimum distance between the supply node 0 and all the demand nodes. Then, the distances found are compared to the values of D_i's, and nodes in V_d that are already accessible are omitted from the initial state s_0. In addition, the demand nodes with $w_i = 0$ are omitted, since these nodes correspond to transshipment (intersection) nodes and, regardless of their accessibility status, do not contribute to the value of the objective function. The cost function defined in Eq. (1) assigns a positive value to an action corresponding to repairing a damaged node that connects new demand nodes to the supply and a zero value when a repair action does not establish accessibility for any demand nodes. When a network is severely damaged requiring to repair multiple nodes to improve accessibility, our DP state network has a significant number of action arcs correspond to zero cost, and only a small subset of actions has a value larger than zero. Implementation of minimum cost algorithms on such networks is inefficient since a lot of actions and nodes have identical values (i.e., equal contribution to the objective function). To facilitate a more

efficient implementation of the DP model, we redefine the cost function as follows:

$$\acute{c}(i_m, t_m, \overline{V_d}, \overline{V_r}, j_m) = \left(\tau(i_m, t_m, \overline{V_r}) + s_j\right). \sum_{kv(\overline{V_d}, \overline{V_r}, j_m)} w_k \qquad (3)$$

Thus, Eq. (3) assigns a cost of going from node i to node j equal to the penalty accrued during that move (plus repair time at node j) for all the demand nodes that have not been accessible at that time. Then, the original recursive Eq. (2) is solved while substituting cost function $c(.)$ with the new cost function $\acute{c}(0)$. Observe that the modified formulation results in exactly the same objective function value, the only difference being how we sum the cost.

Findings

In this section, we evaluate DP algorithm for the NPMCSP. To this end, we use a set of randomly generated instances of the problem. The dynamic programming algorithm was coded in MATLAB in a PC with Windows 10, Core i5, 2.4 GHz CPU and 8GB RAM. In this section, first, we explain the instance generation and then the experimental results will be presented. We use the network generator GNETGEN, which is a modification of the widely used NETGEN generator proposed by Klingman, Napier, and Stutz (1974) and is completely stated in Maya Duque et al. (2016). In order to introduce the procedure, here we briefly explain the instance generation. A minimum cost flow network for a given number of nodes $|V|$ and edges $|E|$ is generated. A supply/demand value is associated for each node and each edge has a cost (travel distance d_{ij}) for being traversed and it is a variable within the interval [0, 10]. By the following procedure, the network is transformed into a network repair. Parameter t_{ij} is generated for each edge e_{ij}, which represents the travel time. This parameter is defined as a function of d_{ij} and an average travel speed

υ as shown in Eq. (4), where r is a uniformly distributed value in the interval [0, 1].

$$t_{ij} = (1 + r)\frac{d_{ij}}{v} \tag{4}$$

Next, the number of damaged nodes $n_d = |V_d|$ is determined. We use a parameter α that specifies the percentage of damage to the network, i.e., the percentage of the edges in the network that are damaged by the disaster. Thus, the number of damaged edges is $n_d = \lceil \alpha|E| \rceil$. We randomly select n_d edges. For each selected edge e: (1) an intermediate point on the edge is randomly chosen, and (2) a damaged node j is created corresponding to that intermediate point. The repair time s_j for the damaged node is set as a random variable uniformly distributed in the interval [10, 60]. (3) The edge e is replaced by two new edges, each of them connecting one of the extremes of edge e and node j. (4) the distance and travel time for each of the new edges depend on the proportion that it represents the original edge e. Finally, for each node i, we must generate the maximum acceptable distance D_i to the depot. That is, the maximum acceptable length of an undamaged or repaired path from i to the depot. The parameter D_i is defined as a function of SP$_i$, the shortest path from i to the depot on the network in which all damaged nodes are repaired (i.e., the pre-disaster conditions). In order to compute D_i, we use a parameter β that represents the maximum tolerable percentage by which the path connecting i to the depot can increase. Thus, for each node i the maximum acceptable distance D_i is defined as $(1 + \beta)$SP$_i$. We consider a set S of small instances, a majority of which can be solved exactly by our dynamic programming model. We use these instances to analyze the performance of the DP approach. Note that, using each one of the minimum cost flow networks generated by GNETGEN, several instances can be created by using different combinations of the parameters α and β. Table 1 shows the number

of nodes considered in the instance, the number of instances generated for each number of nodes, the values used for parameters α and β, and the total number of instances in the set. In order to show the performance of the algorithm, firstly we solve a small instance shown in Fig 2. When no arc (repair node) can be repaired, the maximum demand that can be served is 230 (just demand node 1 can be served). When one repair node is repaired (the first repair node with the shortest path by the depot), the satisfied demand increases to 1160 (repair node 2 is repaired so demand nodes 4, 7 and 8 become accessible). It means that as soon as at least one arc (repair node) is recoverable, a path to nodes 4, 7 and 8 becomes reachable. Note that, we have more than one crew and in this situation arcs 13 and 24 can recover simultaneously and then the satisfied demand increases to 1730 and just demand node 10 is not accessible.
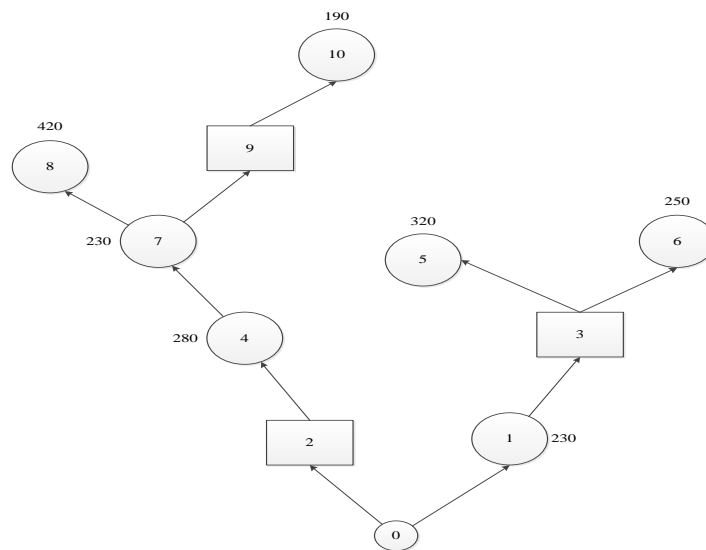

Figure 2.
A Small Network

The dynamic programming model performance is evaluated by a set consisting of 300 small instances. Limiting the maximum computing time to 24 hours for each instance, the algorithm found optimal solutions for 225 of those instances. Table 1 presents the number of instances solved to optimality for each combination of the number of nodes in the network and value of the parameter α, while Table 2 shows the number of optimal solutions found for each combination of the number of nodes and value of the parameter β. The number of optimal solutions found decreases when the number of nodes and the level of damage of the network (α) increase. On the other hand, the number of instances solved to optimality slightly increases when β, the maximum tolerable percentage in which the path connecting i to the depot can augment, increases. We can see from table 2 that by increasing m to 8, almost all number of instances solved optimality. Note that, in this study we don't consider the limitation of the crew availability but it may be a limitation in the real life.

Table 1.

Number of Optimal Solutions Found for Each Combination of the Number of Nodes and Values of α and the Number of Crew Groups (m) (out of 12)

No. nodes	m=1 α					m=2 α					m=4 α					m=8 α				
	5	10	25	30	50	5	10	25	30	50	5	10	25	30	50	5	10	25	30	50
21	12	12	12	12	9	12	12	12	12	10	12	12	12	12	12	12	12	12	12	12
26	12	12	12	12	12	12	12	12	12	12	12	12	12	12	12	12	12	12	12	12
31	12	12	12	11	1	12	12	12	12	4	12	12	12	12	8	12	12	12	12	12
36	12	12	5	3	0	12	12	8	5	2	12	12	11	8	6	12	12	12	12	10
41	12	12	2	2	0	12	12	5	5	2	12	12	9	9	5	12	12	12	12	10

Table 2.

Number of Optimal Solutions Found for Each Combination of the Number of Nodes and Values of β and the Number of Crew Groups (m) (out of 15)

No. nodes	m=1				m=2				m=4				m=8			
	α				α				α				α			
	5	10	25	50	5	10	25	50	5	10	25	50	5	10	25	50
21	14	14	14	15	15	15	15	15	15	15	15	15	15	15	15	15
26	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
31	11	12	12	13	13	13	13	14	15	15	15	15	15	15	15	15
36	6	7	9	10	9	10	11	12	14	14	13	10	15	15	5	12
41	6	6	8	8	9	9	10	10	13	13	11	8	14	14	14	12

Next, we show the performance of the algorithm on two test instances based on the road networks of two districts in Istanbul, Turkey as presented in Aksu and Ozdamar (2014). The first network consists of 212 arcs out of which 49 are damaged and needs to be repaired, while the other network has 386 arcs where 79 are damaged (pictures of this two district are in Aksu and Ozdamar (2014) and interested readers can refer to it). The repair times for damaged arcs (repair nodes) vary between 1 and 10 h. Each instance was allowed a maximum of 3600 s. CPU time.

Table 3.

Computational Results for the First Region

Number of repair Crews (*m*)	Makespan (h)	Number of repaired nodes	CPU time (s)
1	72	21	3600
2	72	27	3600
3	72	32	3600
4	72	35	3207
6	72	38	2704
10	49	49	1232

Table 4.

Computational Results for the Second Region

Number of Repair Crews (m)	Makespan (h)	Number of repaired nodes	CPU time (s)
1	72	23	3600
2	72	30	3600
3	72	35	3600
4	72	44	3600
6	72	52	3600
10	63	79	3600

As stated in Feng and Wang (2003), the first 72 hours after a disaster is a vital time, for all runs, we have used a unit time period of one hour and set the value of T_{max} as 72 periods (hours), which corresponds to three 24-h work shifts. Tables 3 and 4 display the results for two disaster areas under different crew groups. The second column displays the makespan, i.e. the number of periods required to complete the repairing the damaged nodes (arcs). Note that, when the repairing cannot be done within 72h, a value of 72h is entered in the table. The third column is the number of damaged nodes that are repaired at the end of the indicated makespan. Note that, in the first region as we can see from Table 3, just when10 repair crews are available all the demand nodes can be accessible. Also, in the second region just when 10 repair crews are available all the damaged nodes are repaired and all the demand nodes can become accessible. Note that, differences between the numbers of repaired nodes in two regions are because of the topology of their network. This suggests that the problem gets easier as the value of m (number of crew groups) increases. As expected, a higher value of m, also, results in a better objective function value (i.e. total accessible time of demand nodes) as well as a reduced makespan. In the case of the first region, for higher settings of m we see a reduced CPU time requirement. Finally, the results in Tables 1 and 2

suggest that the algorithm can be used to obtain high-quality solutions within a reasonable time. As a result, we can compare the obtained result with Aksu and Ozdamar (2014) as they consider just one crew group with different equipment. We can see that number of repaired nodes and makespan is reduced efficiently in our approach with multiple crew groups.

Conclusion and Future Research

In the occurrence of a disaster, the distribution infrastructure can be seriously damaged, making it impossible or unsafe to execute the response and recovery operations. In this paper, the problem of emergency repair of a network that has been damaged after a disaster is studied. We address the scheduling of multi repair crews, starting from a single depot, while optimizing accessibility to the demand nodes that need relief goods. Our contribution compared to the previous studies is considering the repair crews more than one crew. We adopt a dynamic programming model and discuss efficient implementation techniques that allow us to find optimal solutions for a range of instance sizes of the problem. We compare our results with the same study that considers just one repair crew and it was shown that our approach is working efficiently. Considering more than one depot and heterogeneous fleet are interesting areas for future research. Also, comparing the computational result with some similar algorithms for the crew scheduling problem is a good area which authors are working on it.

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